Computer-Aided Design AND APPLICATIONS
www.cadanda.com

Revolutionizing Digital Marketing Industrial Internet of Things-enabled Supply Chain Management in Smart Manufacturing

Hui Zhang[1*]

[1]School of Economics and Management, Jiaozuo University, Jiaozuo 454000, China
zhanghuihui7880@outlook.com

Corresponding author: Hui Zhang, zhanghuihui7880@outlook.com

Abstract. Industrial Internet of Things (IIoT) deployment in manufacturing units has leveraged their performance assessed by time, productivity, and supply. The integrated smart manufacturing features are handled and organized using conventional IoT for non-intervening efficiency. This article focuses on harmonized supply chain management for smart manufacturing units for augmenting different exceptional connecting and availability improvements. Therefore, this article introduces a Harmonized Supply Management Scheme (HSMS) based on production to delivery routine. The supply allocation and delivery updates are updated from heterogeneous locations to prevent overloaded manufacturing. Besides, the redundant delivery planning across distinguishable supply routes is confined based on demand prioritization. The demand and forecast data is observed from the IoT platform and is processed in the industrial environment for further supply planning. The entire supply and delivery management processes are distinguished using federated learning and IoT accumulated data. This learning paradigm extracts production, supply, demand, and distribution data from diverse locations and identifies a common supply point for optimal planning. The process is repeated before and after the demand satisfaction across different locations and transports. Therefore the learning update improvises the delivery rate and product availability with the cooperative IIoT.

Keywords: Federated Learning, IIoT, Smart Manufacturing, Supply Chain Management; Revolutionizing Digital Marketing
DOI: https://doi.org/10.14733/cadaps.2024.S4.211-228

1 INTRODUCTION

The Industrial Internet of Things (IIoT) is a network that interconnects wireless sensors, things, instruments, and other electronic devices to build an application. IIoT is most widely used for manufacturing and energy management systems. IIoT contains sensors, computers, machines, applications, and technologies. IIoT is also used for smart manufacturing, which requires proper functions and operations [16, 15]. Smart manufacturing is used in industries that ease the work and reduce an organization's workload. Various methods are used in smart manufacturing, which reduces both the time and energy consumption ratio in computation [28]. Resource allocation is a complicated task to perform in smart manufacturing. IIoT is used in allocation that allocates resources based on certain functions and conditions [20]. IIoT provides feasible data which are required for resource allocation that reduces latency in identification and resource classification processes. Hierarchical trustful resource assignment (HTRA) is used in smart manufacturing [26]. HTRA predicts the resources required to perform tasks in industries, enhancing the systems' effectiveness and significance range. HTRA increases the security and feasibility level of smart manufacturing [24].

Supply chain management (SCM) is a process that manages the flow of goods and services in an organization. Smart manufacturing uses SCM to reduce the time and energy consumption ratio in validation and identification processes [1]. Smart manufacturing requires feasible data which provides relevant information for further processes. Smart manufacturing provides various ideas that improve a nation's economic and financial growth. SCM provides appropriate data from the database, which reduce the complexity range in optimization and classification [13]. SCM in smart manufacturing decreases the overall computational cost of the systems. SCM predicts the exact content and meaning of the demands which are available in smart manufacturing. SCM produces final data that provide effective variables and patterns for the products manufactured in an organization [27]. Smart manufacturing increases an industry's production and manufacturing range, enhancing the organization's financial status. SCM manages the key values, partner details, product quality, public feedback, and quality of service (QoS). SCM also secures real-time data which are provided by an organization [21].Digital marketing techniques enable organizations to gather and analyze data from various sources, including customer behavior, market trends, and supply chain operations. By leveraging data analytics and visualization tools, organizations can gain valuable insights into SCM processes in smart manufacturing. These insights can help optimize operations, improve efficiency, and make data-driven decisions.

Artificial intelligence (AI) based techniques and algorithms are used in various fields. AI techniques are mostly used for prediction and analysis processes. AI technique maximizes the prediction accuracy that enhances the systems' and applications' performance and efficiency range [12]. AI is also used for SCM in smart manufacturing systems. The main of AI is to classify the exact content based on variables and patterns. Key values are fetched from SCM that reduce the computation process's error and time consumption ratio [25]. AI-based SCM is used in smart manufacturing that provides necessary data for various functions and processes. SCM produces feasible data for the decision-making process, increasing manufacturing processes' accuracy and efficiency [17]. AI technology is mainly used in smart manufacturing to get effective information and advantages to production. AI techniques reduce the waste and misstate range in smart manufacturing, improving product quality and QoS [3]. AI solves unwanted problems and issues which are occurred during the optimization and computation process. AI enhances smart manufacturing systems' overall effectiveness and robustness [19].

2 RELATED WORKS

Cao et al. [5] introduced an ontology-based holonic event-driven architecture (EDA) for autonomous manufacturing systems. EDA enables organizations to be integrated and configured, providing appropriate event resources. EDA follows event access rules which produce certain rules for manufacturing systems. The ontology model reduces the complexity ratio in computation, improving the systems' performance. The introduced EDA architecture maximizes the systems' feasibility, flexibility, efficiency, and reliability.

Zhang et al. [29] designed a green closed-loop supply chain with fairness concerns for the manufacturing system. The main aim of the proposed method is to identify the waste products and resources which are presented in the manufacturing system. Fairness concerns provide optimal data, which increases accuracy in the waste identification process. Fairness concerns increase the accuracy of decision-making, enhancing the systems' effectiveness. The proposed model reduces the damages, improving green closed-loop supply chain efficiency.

Al-Rakhami et al. [2] developed a provenance-aware traceability framework (ProChain) for the Internet of Things (IoT) based supply chain system. The proposed framework is mostly used to solve problems and issues which are occurred during computation and optimization processes. Wireless sensors are used here that provide feasible data to identify problems. Experimental results show that the proposed framework ensures the safety and security of the systems.

Burgess et al. [4] proposed a blockchain-based quality management architecture for a short food supply chain system. The food supply chain faces various problems and quality check issues. The proposed architecture detects the issues and solves the issue based on certain functions and conditions. Blockchain architecture specifies the database's content, reducing the systems' latency and computational costs. The proposed architecture enhances the overall performance and quality of the service range of short food supply chain systems.

Esmaeilian et al. [6] designed blockchain technology for a sustainable supply chain management system in industry 4.0. Internet of Things (IoT) is also used here that enable the manufacturer to understand the exact behaviors and scenarios of users. Development and computation costs are reduced, which improves the efficiency of supply chain management systems. The proposed blockchain technology increases the sustainability, robustness, and effectiveness ratio of industry 4.0.

Jamrus et al. [10] introduced a dynamic coordinated scheduling framework for a supply chain manufacturing system. The main aim of the proposed framework is to address the manufacturing problems which are presented in a system. Dynamic features and factors that produce relevant data for the detection process are analyzed. When compared with other frameworks, the introduced framework achieves high accuracy in issue prediction. The introduced framework increases the performance and efficiency of the systems.

Zhou et al. [30] developed a field-programmable gate array (FPGA) and Internet of Things (IoT) based logistics supply chain information collaboration. FPGA is mainly used for analysis that provides feasible supply chain information for the collaboration process. IoT reduces the complexity range in identification, enhancing the systems' feasibility. The proposed method reduces the overall computational cost and time consumption in performing certain tasks in collaboration systems

Gunduz et al. [8] developed a hybrid best-worst method (BWM) and quality function deployment (QFD) for the supply chain management. Smart and sustainable tools are used in the proposed method that addresses the maturity ratio of functions. The main aim of the proposed method is to identify the relationship among functions in supply chain systems. Experimental results show that the proposed method improves the efficiency, sustainability, and feasibility range of supply chain management systems.

Shao et al. [23] proposed a multistage implementation framework for smart supply chain management in industry 4.0. Supply chain management is a complicated task to perform in every industry. The proposed implementation framework provides various services that reduce the workload and error range in industry 4.0. Multistage implementation framework enables certain functionalities which reduce the complexity ratio of smart supply chain systems.

Pu et al. [18] designed an agent-based supply chain (SC) allocation model for SC management systems. The proposed model is a dynamic allocation planning which provides necessary plans for

SC management systems. The proposed model is mostly used in smart manufacturing companies and enterprises. Agent technology utilizes SC values which provide optimal data allocation process. Compared with other models, the proposed model enhances management systems' capabilities, sustainability, and efficiency.

Jiang et al. [11] proposed a production and maintenance strategy for a service-oriented manufacturing supply chain system. The proposed strategy is mainly used to address the issues which are presented in the system. Channel coordinates, patterns, and factors are detected from the database, providing feasible data for further optimization and computation processes. The proposed strategy increases decision-making accuracy, improving the effectiveness and feasibility range of manufacturing supply chain systems.

Sarkar et al. [22] designed a supply chain management model. The main aim of the proposed model is to control the random lead time demand in supply chain systems. Three types of inspections are conducted on every system that identifies important patterns and features. The extracted feature produces necessary information for the supply chain management. The proposed models reduce the computation cost and latency range, increasing the products' quality ratio.

Kuo et al. [14] developed a material resource management and allocation approach for a smart supply chain system using hybrid industry 3.5 strategies. An information-sharing technique is used here that shares the relevant information which is required for the allocation process. Manufacturers get information from information sharing that enhances accuracy in the decision-making process. Information sharing reduces both time and energy consumption range in the computation process. The proposed approach enhances the overall performance and feasibility of the systems.

Fierro et al. [7] proposed a colored Petri nets-based multi-agent approach for a supply chain management system. Colored Petri net provides optimal data, which is required for management systems. An analysis method is used here that analyzes the datasets which are presented in the database. Petri nets reduce latency and error in the computation process. Experimental results show that the proposed approach reduces complexity, increasing the systems' efficiency and sustainability.

3 PROPOSED HARMONIZED SUPPLY MANAGEMENT SCHEME

The proposed HSM scheme is designed to improve the product availability and delivery rate in the cooperative IIoT based on product production, supply, and transportation changes to integrate supply chain management. The important computable factors in this scheme, such as supplier selection process, smart manufacturing, cost-efficient supply chain management, and market vehicle values, are considered to augment faster logistic deliveries and parcel exchange. Multiple sensors are used to gather the information observed from logistic-carrying vehicles. The information's vehicle engine temperature, RPM, and vibration in the wheel are used to analyze abnormalities of the logistic vehicles. The current potential supplier for new customers is matched with the potential supplier for existing customers to prevent uncertainty and the possibility of human error. The gathered data is analyzed with the aid of IIoT to identify failures in the logistic vehicles. Based on the shipment, processing time and easy supply distribution differ for each product. The purchasing organization is analyzed and stores the production, supply, and transportation data, which can differ over time. Product manufacturing, logistic vehicles, and supply distribution are jointly analyzed to improve smart manufacturing, and its stability can be estimated. Therefore, this smart manufacturing stability estimation based on data accumulation and response between smart industries and IoT platforms is considered to increase supply chain management with less analytical complexity. In Figure 1, the process of the proposed scheme is illustrated.

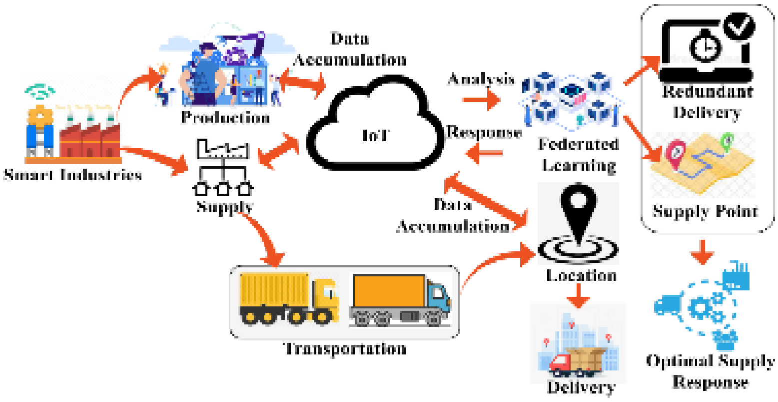

Figure 1: Process of the Proposed Scheme.

With the aid of conventional IoT and federated learning, the customer location is required to deliver the parcel to the individuals. This will help the customer to save time and reduce potential failure, transportation failure, and common supply points in the industrial process. Based on customer satisfaction is identified to improve HSM with a large number of logistic vehicles. An IIoT-assisted vehicle performs the order collection, packaging, and warehouse processing time. The cost function in HSM with IoT-based logistic vehicles used for product delivery. The IIoT-based proposed scheme offers lower but comparable costing for a small number of vehicles, whereas for a large number of vehicles with moderate cost increases.

The productivity and parcel exchange is analyzed for non-intervening efficiency computation through federated learning. Federated learning is classified as redundant delivery and supply point for gaining optimal supply response. The production-to-delivery routine is monitored and analyzed for improving various exceptional connecting and availability improvements. The supply allocation and delivery updates observed from heterogeneous locations are analyzed based on customer demand prioritization. In particular, the exceptional connecting and availability improvements are computed based on applying a redundant delivery plan to prevent overloaded manufacturing. This federated learning improves redundant delivery and reduces failures in smart manufacturing scenarios.

The function of HSMS in smart manufacturing based on production, supply allocation, and delivery update data is observed from all smart industries and is analyzed. The supply chain management is improved with optimal supply response and its accumulated data analysis through federated learning. The supply allocation and delivery process updates for precise product shipment, and the modifications in supply, production, and delivery are changed using federated learning. The federated learning outputs in maximum supply point and redundant delivery based on customer demand priority. HSMS is used to analyze the product production to delivery routine in smart manufacturing scenarios for reducing overloaded manufacturing. The sensed data from heterogeneous locations are initially processed for analyzing the logistic carrying vehicles' condition. The smart industries data is observed and processed for computing non-intervening efficiency is expressed as

$$Ef_{int} = \frac{1}{t}\left\|\sum_{n=1}^{t} PD_i(d) + SP_j(d) + TR_k(d)\right\| \tag{1}$$

Such that,

$$PD_i(d) = \frac{1}{at}\int_{-\infty}^{\infty} \frac{\frac{PD_i(d)}{D_{dl}} n(p^{ex})}{at} \, d.at \tag{2}$$

$$SP_j(d) = \frac{1}{at}\int_{-\infty}^{\infty} \frac{SP_j(d) n(p^{ex})}{at} \, d.at \tag{3}$$

$$TR_k(d) = \frac{1}{at}\int_{-\infty}^{\infty} \frac{TR_k(d)}{at} d.at \tag{4}$$

Above equations (1) to (4), the variables $PD_i(d)$, $SP_j(d)$ and $TR_k(d)$ represents the production, supply, and transportation information observed from the sensors with different sensing intervals for improving non-intervening efficiency Ef_{int} . The integrated smart manufacturing features are organized to analyze accumulated data i, response j, and delivery data k. The data accumulation d based on supply allocation and delivery updates is processed. Similarly, the total number of parcel exchanges or distribution $n(p^{ex})$ in the individual smart industry is assessed and estimated by any time interval at. The data accumulation and distribution processes are portrayed in Figure 2.

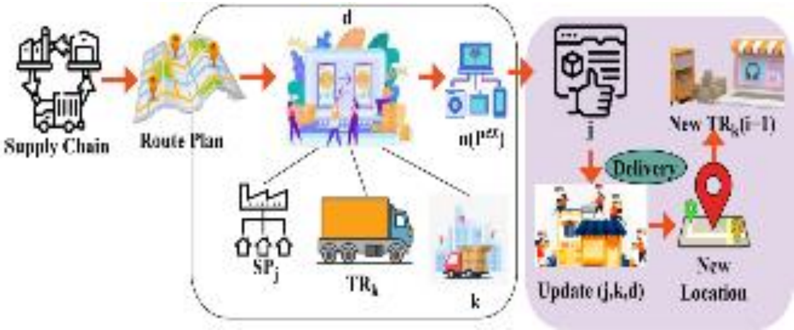

Figure 2: Data Accumulation and Distribution.

The supply chain management requires a proper route plan using SP_j, TR_k, and $k \, \forall \, d$. This d is updated post $n(p^{ex})$ over the varying route plans. Based on the j, the update (j,k,d) is cumulatively performed. This update is performed post new $TR_k(i+1)$ such that precise data is available (Figure 2). If i, j and k are maximized and minimized for accumulated data analysis, therefore $i \in [0,\infty]$, $j \in [-\infty, 0]$ and $k \in [\infty, -\infty]$ is computed to measure the customer purchase lifetime value Cp_L from the IIoT is expressed as

$$\mathrm{Cp_L} = \sum_{\mathrm{t}}^{\mathrm{TR}} \frac{\delta(\mathrm{Prdt_{purchase}})_{\mathrm{Nt}} - \delta(\mathrm{Max_{opc}})_{\mathrm{Nt}} - \mathrm{Max_{mrkt_{Nt}}}}{(1+\mathrm{Dic_r})} \tag{5}$$

In equation (5), the constraints $\delta\left(Prdt_{purchase}\right)_{Nt}$, $\delta\left(Max_{opc}\right)_{Nt}$ and $Max_{mrkt_{Nt}}$ illustrates the profit from products purchased by N customer at different time intervals t, the maximum operating cost of N customer, and the maximum marketing cost for N customer. The first customer lifetime value for purchasing products online is computed based on supply allocation and delivery updates in IoT. The exceptional connecting and availability improvement is analyzed and improved based on the production-to-delivery routine in all the smart industries. Here, the discount rate Dic_r is estimated for all products. The forecast data and demand is observed from the IoT platform, and updates to the information are based on the extraction of current product production, supply, demand, and distribution data from different locations. Modifications in supply allocation and delivery updates due to demand prioritization, customer changing their location, or any problems in transportation are identified. The harmonized supply chain functions for improving Ef_{int} in different time intervals.

These smart manufacturing units' processing sequence follows high data accumulation and response that is analyzed for planning redundant delivery at a given time interval and is estimated as

$$\left.\begin{array}{c} D_A(t) = \frac{PD_i(d)}{t} * 2^{\frac{f}{2}} LCV_x\left(Ov \times t - 2^f\right) \\ and \\ R_S(t) = \frac{SP_j(d)}{t} * 2^{\frac{f}{2}} LCV_y\left(Ov \times t - 2^f\right) \end{array}\right\} \quad (6)$$

Where,

$$\left.\begin{array}{c} LCV_x = S^{pd}(t) \left\|\frac{f}{2}\right\| TR(t)_{Ov-1} \\ and \\ LCV_y = S^{pd}(t)^{-1} \left\|\frac{f}{2}\right\| TR(t)_{Ov-1} \end{array}\right\} \quad (7)$$

Where the integrated smart manufacturing features, such as accumulated data D_A and response R_S from the IoT platform is analyzed continuously for improving supply chain management. Based on the supply allocation, small LCV_x and large LCV_y logistic carrying vehicles are provided for distribution. Similarly, the variables $S^{pd}(t)$ and $S^{pd}(t)^{-1}$ used to denote the successful product delivery and failed delivery based on i and j is analyzed. The failure f and overloaded manufacturing Ov are identified for controlling supply routes. The failed delivery is again delivered with an accurate location through federated learning for updating the customer's current location. Now, the redundant delivery planning for accumulated data analysis is expressed as

$$Ef_{int}[S^{pd}(t)] = \frac{2^{\frac{f}{2}}[(Ov \times t) - 2^f]}{t^2} [LCV_x + LCV_y] \quad (8)$$

$$= \frac{2^{\frac{f}{2}}}{t}\left[\int_0^{\infty} \frac{LCV_x[(Ov \times t) - 2^f]}{t} d.at - \int_{-\infty}^{0} \frac{LCV_y[(Ov \times t) - 2^f]}{t} d.at\right] \quad (9)$$

As per the equation (8) and (9), the data analysis of the aforementioned failure-less supply distribution $Ef_{int}[S^{pd}(t)]$ is processed through federated learning. After the supply allocation and delivery location is updated for identifying and reducing overloaded manufacturing at different time intervals. The learning process is presented in Figure 3.

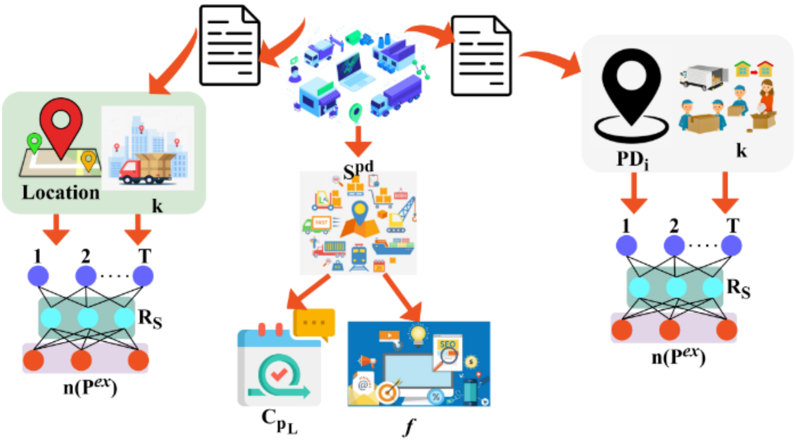

Figure 3: Learning Process.

The learning relies on R_S and $T \forall n(p^{ex})$ from different PD_i and k instances. Considering the learning across different $D_A(t)$, the $n(p^{ex})$ is used for improving the supply chain. The requirements for R_S such that $S^{pd}(t)$ is achieved through distinguishable R_S. If R_S is not distinguishable, then k data $\forall SP_j$ and PD_i is required for improving additional analysis. Therefore, the learning is recurrent for improving the distribution (Figure 3). From this sequence, the sensed data from the smart industry can be classified into two segments: production and supply are analyzed for further supply planning. The above equations used to match the current production and supply data (π_d) with previously accumulated data (σ_d) is computed as

$$\left.\begin{array}{c}\pi_d = \frac{1}{2N(f\times t)}\left|\sum_{i=1}^{t}(PD_d - SP_d)S^{pd^{\theta}}\right|, \forall\, k = i+1, j \in f \\ and \\ \theta_d = -\sum_{i=L_d}^{h_d}\pi_d \log SP_{d_i}\end{array}\right\} \tag{10}$$

In equation (10), the variable θ indicates the common supply point identification at different locations for optimal planning. Where h_d and L_d are the high demand and low demand from the smart industry identified. The data analysis of π_d identifies θ_d for the $Ef_{int}[S^{pd}(t)]$ is computed as in equation (11)

$$\theta_d\left[Ef_{int}\left(S^{pd}(t)\right)\right] = \frac{\pi_d}{log\left[\frac{t}{h_d - L_d}\right]} \tag{11}$$

Contrarily, the smart industries address the aforementioned failures and overloaded manufacturing using federated learning for redundant delivery with a common supply point based on demand analysis. The irrelevant data sensed from the industry caused redundant delivery $(RDD_{delivery})$ is expressed as in equation (11)

$$\left.\begin{array}{c}RDD_{delivery}\left[\theta, t, Ef_{int}\left(S^{pd}(t)\right)\right] = -\sum_{i=1}^{f}PD_i - \sum_{j=1}^{t}SP_j - \sum_{i=1}^{t}\sum_{j=1}^{t}TR_k h_d \\ Instead \\ RDD_{delivery}\left(\theta\left(Ef_{int}\left(S^{pd}(t)\right)\right), \pi_d\right) = \begin{cases} -\sum_{t=1}^{Ov}TR_k\theta_i\frac{1}{LCV_x}, if\ i(t) \in [0,\infty] \\ -\sum_{t=1}^{Ov}TR_k\theta_j LCV_y, if\ j(t) \notin [0,\infty] \end{cases}\end{array}\right\} \tag{12}$$

This redundant delivery issue is prevented through a common supply point for optimal supply response based on $\pi_d\left[Ef_{int}\left(S^{pd}(t)\right)\right]$ and θ_d for individual demand analysis at different time intervals. The learning paradigm helps to address redundant product delivery due to false supply allocation and delivery updates. The entire supply and delivery management process is analyzed depending on θ_d and $\pi_d\left[Ef_{int}\left(S^{pd}(t)\right)\right]$ using federated learning and IoT accumulated data. In this sequential process, the integrated smart manufacturing features are independently analyzed at each for augmenting non-intervening efficiency. The demand satisfaction DM_s across various locations and transports is defined as per equations (13) and (14) for achieving both θ_d and $\pi_d\left[Ef_{int}\left(S^{pd}(t)\right)\right]$ and the following sequence is expressed as

$$DM_s[\theta_d, t] = \frac{Ov^{-RDD_{delivery}\left[\pi_d, t, Ef_{int}\left(S^{pd}(t)\right)\right]}}{\sum_{k=1}^{f\times t}Ov^{-RDD_{delivery}\left[\pi_d, t, Ef_{int}\left(S^{pd}(t)\right)\right]_i}} \tag{13}$$

In equation (13), $RDD_{dellivery}[.]$ represents the redundant delivery operation in both θ_d and $DM_s[.]$ is the initial processing instance at t intervals. Similarly, the learning paradigm extracts initial production, supply, demand, and distribution information analysis, and forecast data are expressed as

$$DM_s\left(\pi_d\left(Ef_{int}\left(S^{pd}(t)\right)\right)\right) = \frac{f^{-RDD_{delivery}\left[\pi_d, t, Ef_{int}\left(S^{pd}(t)\right)\right]}}{\sum_{k=1}^{t} f^{-RDD_{delivery}\left[\pi_d, t, Ef_{int}\left(S^{pd}(t)\right)\right]_i}} \quad (14)$$

The above equation computes the learning paradigm extracted data and its supply point for satisfying the customer demand such that $RDD_{delivery}\left[\pi_d, t, Ef_{int}\left(S^{pd}(t)\right)\right]$ is computed to satisfy both the instance of production and supply. The industrial environment analysis helps to distinguish the supply routes based on industrial performance assessing time for optimal planning. The learning paradigm extracted data is processed through federated learning depending on availability improvements and exceptional connectivity. The constraints $i \in [0, \infty]$, $j \in [-\infty, 0]$, and $k \in [\infty, -\infty]$ satisfy optimal supply response that indirectly represents redundant product delivery at a different time interval. The optimal planning for $Ef_{int}\left[Ef_{int}\left(S^{pd}(t)\right)\right]$ is alone analyzed for achieving maximum demand satisfaction, whereas the different demands $DM_s[.]^*$ from the customer is identified for achieving optimal supply response and controlling supply routes based on demand priority. Therefore, the previous smart industry data handle conventional IoT for further planning. Based on the condition, $k \in [\infty, -\infty]$ is considered. Besides, the redundant delivery planning is computed for minimizing overloaded manufacturing based on accumulated and extracted data from the smart industry and is analyzed for the condition. The efficiency improvement post the common point detection is presented in Figure 4.

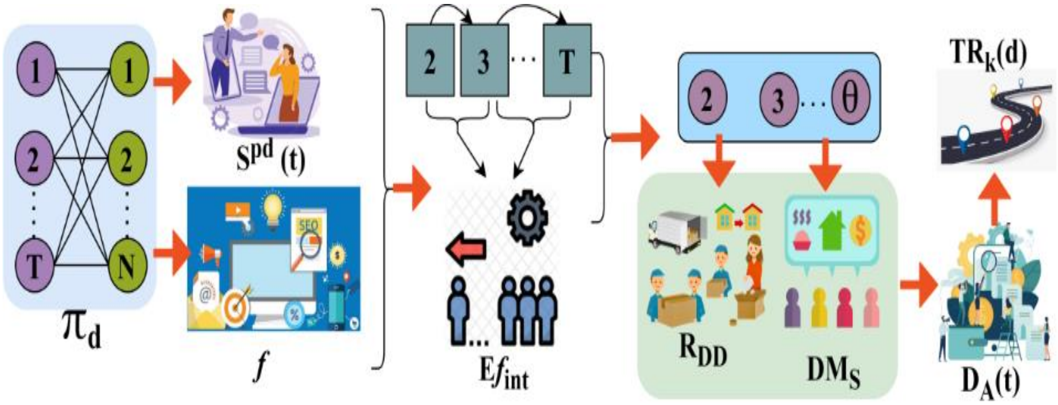

Figure 4: Efficiency Improvement and Common Point Detection.

The $\pi_d \,\forall\, T \times N$ is used for classifying S^{pd} and $f \in t$ under distinguishable j. This is identified in multiple $T\,\forall$ redundancy checks and hence Ef_{int} (as is equation (8)] is estimated. Therefore the RDD and DM_S are handled using θ identified for maximizing delivery. Further, (i, j) is accumulated and analyzed for $TR_K(d)$ (Figure 4). The delivery rate and product availability are computed for improving supply chain management efficiency at the different intervals for further data analysis, and therefore, the accumulated data is not prolonged for failure identification. Further planning is used to forecast data and demand between smart industries and IoT platforms based on t. The demand satisfaction is maximized for optimal planning without increasing the assessing time and failures. The remaining data maximizes processing time based on supply and productivity to prevent overloaded manufacturing in smart industries. The changes in demand and supply distribution are updated using federated learning. Hence, the maximum delivery rate and product availability are computed to improve the supply chain and thereby reduce failures.

4 RESULTS AND DISCUSSION

The proposed scheme is analyzed using the data provided in [30]. The data for location, production, demand, and distribution are used for analyzing the proposed scheme's performance. A cumulative set of 160 entries of the same is used for validating the scheme's efficiency. Based on the demand factor, the analysis for SP_j R_S are independently analyzed in Figure 5.

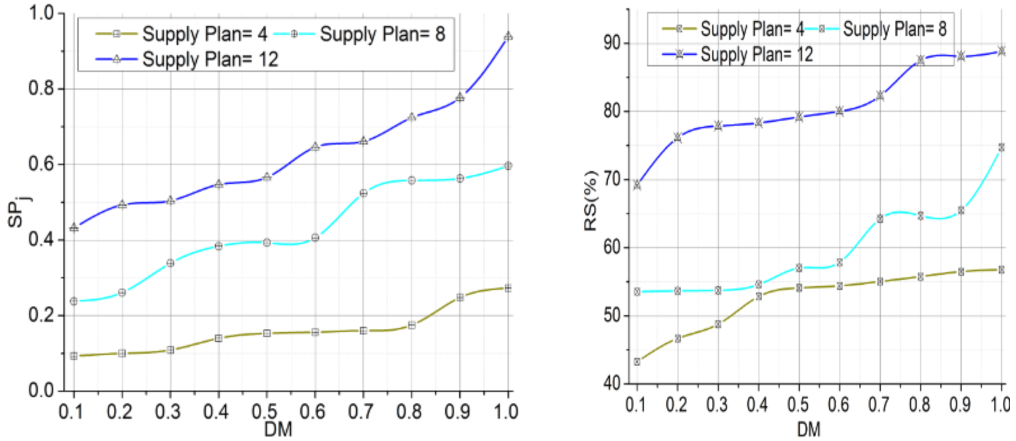

Figure 5: SP_j and R_S Analysis.

The demand optionally increases the chances for SP_j and R_S from the available supply plan. This supply plan is the combination of PD_i, SP_j and $TR_k \forall t$. Therefore the $n(p^{ex})$ is either modified or increased to meet the DM_s. Hence the learning identifies $D_A(t)$ or θ_d based on multiple factors over the distribution. This increases the R_S from different locations along the f. This requires a changed route plan that is preferred using θ and π_d $(previous)$. The change requirement process is illustrated in Figure 6.

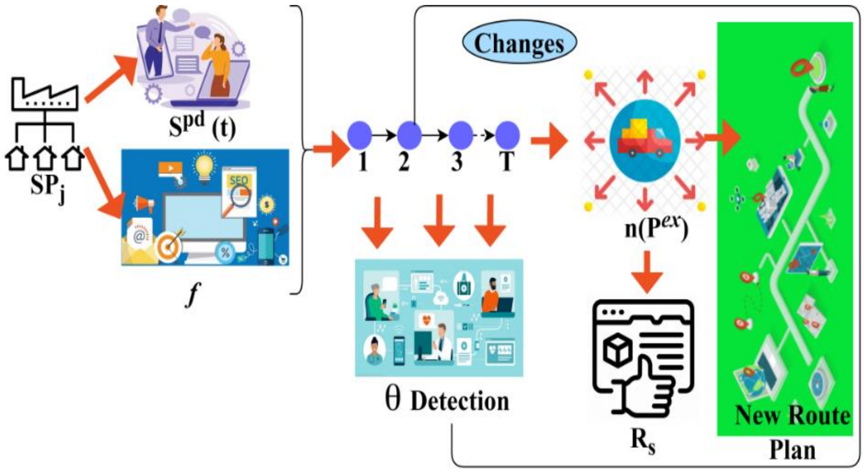

Figure 6: change Requirement Process.

As the f increases as an adverse of $S^{sp}(d)$, the change in $n(p^{ex})$ is required. Considering the θ detection across multiple T, the new route plan through $TR_k(d)$ is formulated. From the given data in [30], the actual delivery and succeeded delivery for the various T are analyzed in Figure 7.

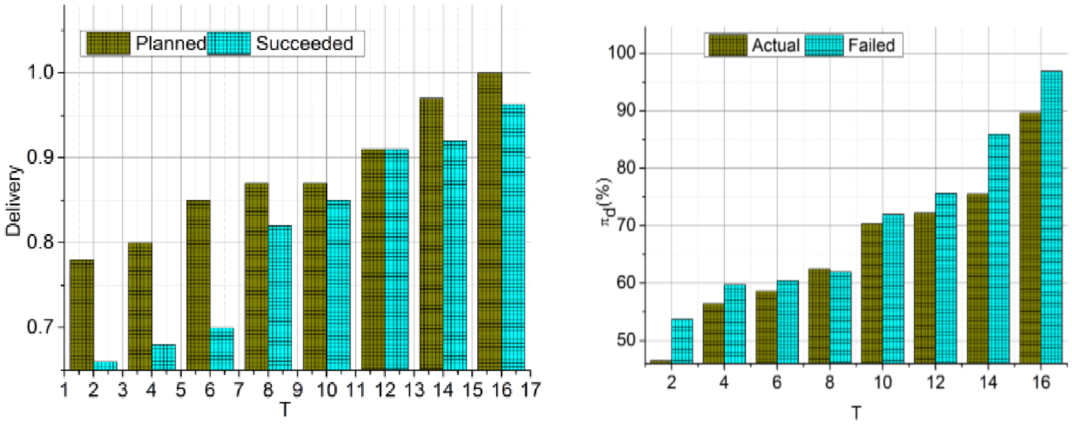

Figure 7: Delivery and π_d Analysis.

The T requirements are stabilized for maximizing various deliveries through multiple classifications. The θ detected improves the chances for $n(p^{ex})$ for better delivery and less failure. Therefore due to additional wait time or unavailability, the R_S is less compared to the actual distribution. Therefore the combination of $(i, j, and\ d)$ are cumulatively analyzed for mitigating f in the alternate plans. The θ and DM_S for the varying $t \in T$ is analyzed in Figure 8.

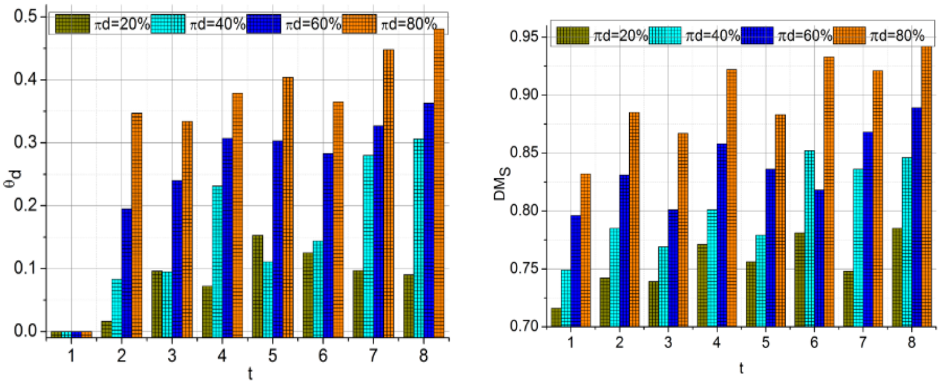

Figure 8: θ and DM_S Analysis.

The θ identification varies with the t between consecutive T such that the Ef_{in} is retained over d. In the learning update, the redundant locations are precisely identified for preventing f in the consecutive T. Therefore the DM_S satisfaction varies with the available inputs (i.e.) PD_i, SP_j and TR_k across multiple R_S. This R_S from σ_d is exploited in modifying T through t. Thus DM_S is independently maximized for the varying plans by identifying θ (Figure 8).

4.1 Comparative Analysis Section

Based on the above discussion, a comparative analysis is presented for the metrics of delivery rate, product availability, demand satisfaction, redundancy, and processing time. The variants are data accumulation (up to 100%) and supply plan (up to 14). The considered methods along the proposed scheme are MRM+AA [28], BWM+QFD [23], and ProChain [18].

4.2 Delivery Rate

This proposed scheme achieves a high delivery rate in different manufacturing units based on product availability and supply distribution for improving supply chain management (Refer to Figure 9). The redundant delivery planning is made for multiple supply routes for demand prioritization is mitigated due to high supply allocation and delivery. The learning process identifies the overloaded manufacturing and redundant delivery in smart manufacturing units. Based on the augmenting different exceptional connecting and availability improvements are analyzed with the previous supply distribution data.

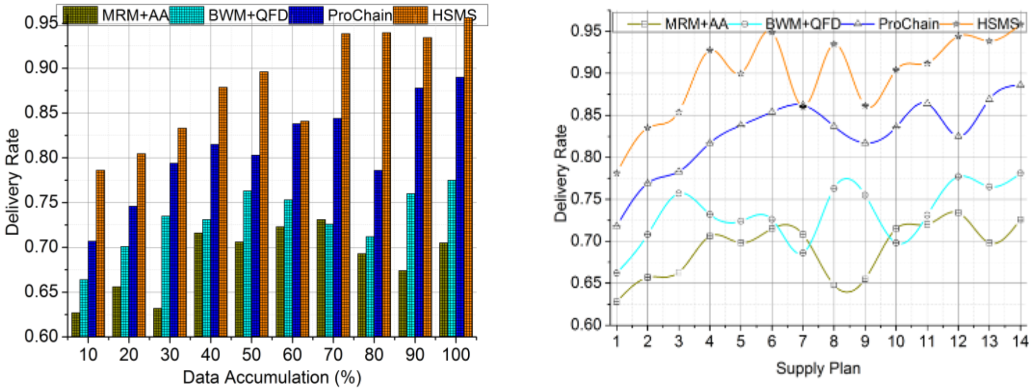

Figure 9: Delivery Rate Analysis.

This computation is performed for decision-making in both instances. Therefore, the identification of failure in smart manufacturing units improves the demand-supply point for preventing high processing time for accumulated data analysis, and hence optimal supply response is achieved. The different productivity and supply information is analyzed for further supply planning to prevent overloaded manufacturing. Therefore, the first production and supply are processed using the conditions $i \in [0, \infty]$, $j \in [-\infty, 0]$, and $k \in [\infty, -\infty]$, the data accumulation from the IoT used to satisfy two different conditions for retaining the redundancy factor in this article. The proposed scheme analyzes the integrated smart manufacturing features to maximize product availability.

4.3 Product Availability

The product availability is high in this proposed article for improving smart manufacturing based on production to delivery routine is performed continuously and compared the features to other factors (Refer to Figure 10). In this manuscript, the data accumulation is analyzed for increasing product delivery rate through federated learning and reducing redundant delivery at any time interval. The non-intervening efficiency is improved based on a high delivery rate and product availability is achieved [as per equation (1)].

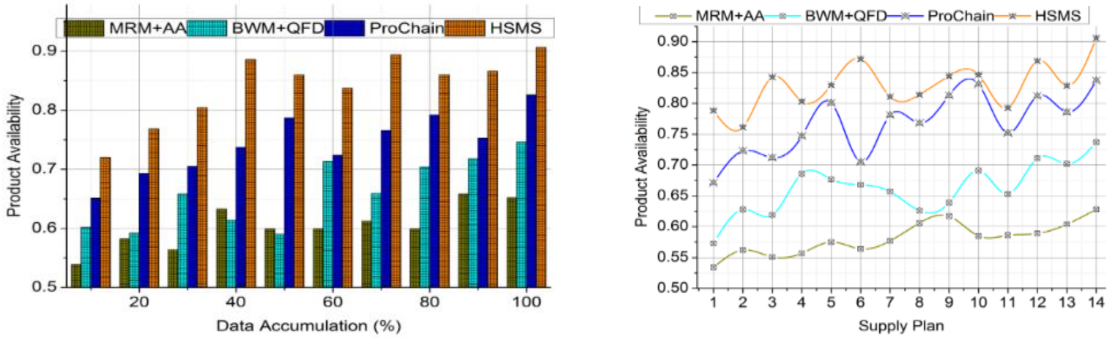

Figure 10: Product Availability Analysis.

The supply allocation and delivery updates are updated for identified sequence changes to augment product availability and exceptional connecting. In this proposed scheme, redundant delivery and supply point is identified for retaining that factor. Based on the data accumulation, the productivity and supply are computed in smart manufacturing to perform a continuous production to delivery routine. In this article, demand prioritization relies on accumulated data analysis; therefore, the harmonized supply chain management achieves less redundant delivery.

4.4 Demand Satisfaction

In Figure 11, the locations and vehicles' condition is verified for precise product delivery and the number of parcel exchange or supply distribution $n(p^{ex})$ in the individual smart industry is estimated at different time intervals at. The customer lifetime value for purchasing is also computed based on supply allocation and delivery update is observed from the IoT platform.

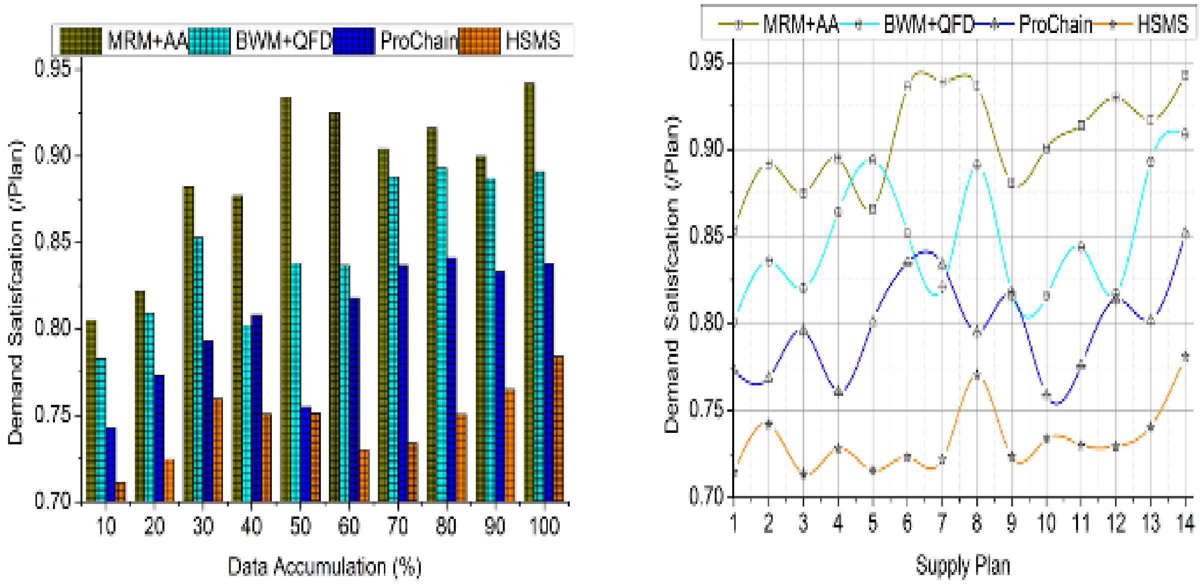

Figure 11: Demand Satisfaction Analysis.

In smart industries, overloaded manufacturing and redundant delivery are identified through federated learning. The forecast data and demand observed from the IoT platform are used to update the previous data with current product production, supply, demand, and distribution data at different locations. The federated learning and IoT accumulated data is processed for achieving optimal response from the IoT to smart industries with the condition of $\delta(Prdt_{purchase})_{Nt}$ and $Max_{mrkt_{Nt}}$ is computed continuously. The manufacturing units and data utilization is identified through the learning process. This analysis is performed to prevent failures and redundant delivery based on the common supply point in smart industries.

4.5 Redundancy

The demand satisfaction across different locations and transportation are identified for ease of performing production to delivery in a routine manner for improving supply chain is illustrated in Figure 12. In this proposed smart manufacturing satisfies less redundancy in delivery is computed with available demand and forecast data through federated learning at different teaching intervals. In this instance, failure and overloaded manufacturing is addressed to prevent redundancy, followed by the common supply point based on demand prioritization.

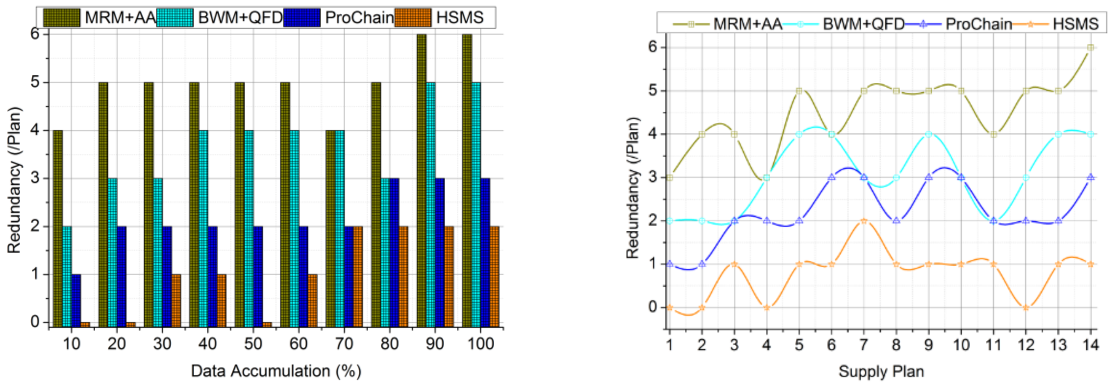

Figure 12: Redundancy Analysis.

The redundancy is mitigated due to identifying failures in parcel delivery, whereas the optimal planning is made for precise supply response during smart manufacturing is preceded using the above equation (6), (7), (8), (9), (10), and (11). The product availability and delivery rate in this proposed scheme are computed to enhance harmonized supply chain management. Instead, the accumulated data analysis for continuous manufacturing of products in smart industries prevents redundancy through learning. Based on the redundant delivery planning, the demand prioritization is confined.

4.6 Processing Time

In Figure 13, the learning extracts data from the IoT platform and then analyzes it for processing smart industries at different time intervals. Based on the manufacturing features, the production and supply are performed from heterogeneous locations to reduce overloaded manufacturing and redundant delivery in smart industries. The accumulated data from the IoT platform is analyzed through federated learning for improving supply chain management as it does not require a demand-supply point for redundant delivery is identified through the learning process.

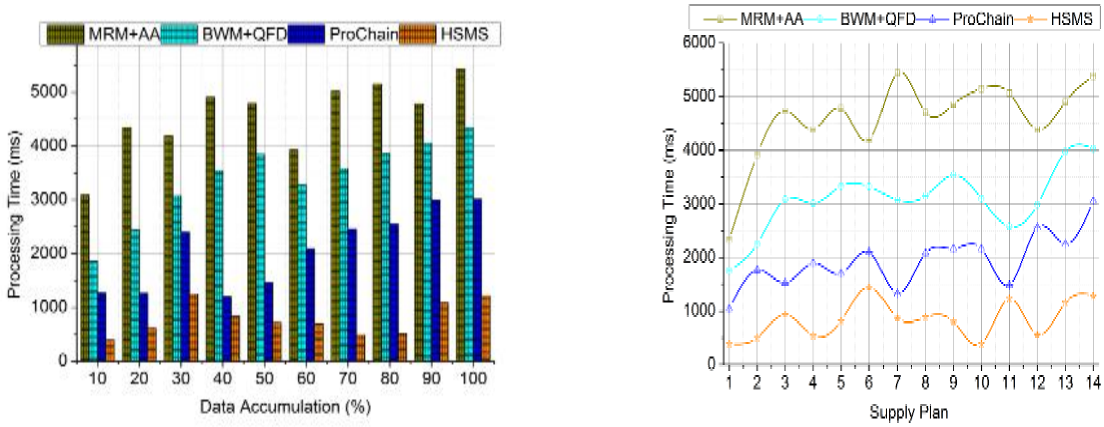

Figure 13: Processing Time Analysis.

The demand and forecast data analysis is processed for all supply and delivery management. The aforementioned failures and overloaded manufacturing are addressed using federated learning for identifying redundancy and retained with a common supply point based on demand analysis. This overloaded manufacturing is addressed in smart industries leading to high processing time and demand prioritization. If accumulated data is analyzed in this model and hence high supply point is achieved. The successful production to delivery is performed by the proposed scheme, for which the proposed model satisfies less processing time. The comparative analysis results are presented in the following Tables 1 and 2.

Metrics	*MRM+AA*	*BWM+QFD*	*ProChain*	*HSMS*
Delivery Rate	*0.705*	*0.775*	*0.891*	*0.9564*
Product Availability	*0.652*	*0.746*	*0.826*	*0.9064*
Demand Satisfaction (/Plan)	*0.942*	*0.891*	*0.838*	*0.7842*
Redundancy (/Plan)	*6*	*5*	*3*	*2*
Processing Time (ms)	*5427.18*	*4339.72*	*3013.8*	*1218.02*

Table 1: Comparative Analysis Results (Data Accumulation).

Findings: The proposed scheme improves delivery rate by 8.3%, product availability by 8.25%, and demand satisfaction by 10.61%. HSMS reduces redundancy and processing time by 9.52% and 11.9%, respectively.

Metrics	*MRM+AA*	*BWM+QFD*	*ProChain*	*HSMS*
Delivery Rate	*0.726*	*0.781*	*0.886*	*0.9584*
Product Availability	*0.628*	*0.737*	*0.837*	*0.9062*
Demand Satisfaction (/Plan)	*0.943*	*0.909*	*0.852*	*0.7814*
Redundancy (/Plan)	*6*	*4*	*3*	*1*
Processing Time (ms)	*5385.0*	*4030.49*	*3054.65*	*1288.71*

Table 2: Comparative Analysis Results (Supply Plan).

Findings: The proposed scheme improves delivery rate by 8.04%, product availability by 8.71%, and demand satisfaction by 11.99%. HSMS reduces redundancy and processing time by 12.83% and 11.5%, respectively.

5 CONCLUSION

A harmonized supply management scheme by integrating the industrial internet of things and federated learning is proposed and discussed in this article. This scheme is designed to improve the demand satisfaction level of various distributions by accounting for the failure and redundancy in supply plans. To retain the routines' sustainability across multiple locations, the precise production, demand, and delivery data are accumulated through different responses and IoT devices. This information is classified for identifying common supply points for precise delivery management and prioritization. Therefore, consecutive deliveries are planned accordingly with fewer failures. In this classification and data analysis, federated learning is introduced such that the accumulated data is used for non-redundant deliveries and non-overloaded manufacturing. Therefore, the efficiency in the previous and current route plans is validated using supply and response data to prevent location dropouts across multiple plan intervals. The proposed scheme improves delivery rate by 8.3%, product availability by 8.25%, and demand satisfaction by 10.61%. HSMS reduces redundancy and processing time by 9.52% and 11.9%, respectively.

Hui Zhang, https://orcid.org/0000-0002-6271-7395

REFERENCES

[1] Alqahtani, F.; Al-Maitah, M.; Besoul, K.; Elagan, S. K.: Elastic computing resource virtualization method for a service-centric industrial internet of things, Computer Networks, 190,2021, 107955. https://doi.org/10.1016/j.comnet.2021.107955

[2] Al-Rakhami, M. S.; Al-Mashari, M.: ProChain: Provenance-aware traceability framework for iot-based supply chain systems, IEEE Access, 10, 2021, 3631-3642. https://doi.org/10.1109/ACCESS.2021.3135371

[3] Bruzzone, A. G.; Massei, M.; Frosolini, M.: Redesign of supply chain in fashion industry based on strategic engineering, Procedia Computer Science, 200, 2021, 1913-1918. https://doi.org/10.1016/j.procs.2022.01.392

[4] Burgess, P.; Sunmola, F.; Wertheim-Heck, S.: Blockchain enabled quality management in short food supply chains, Procedia Computer Science, 200, 2022, 904-913. https://doi.org/10.1016/j.procs.2022.01.288

[5] Cao, H.; Yang, X.; Deng, R.Ontology-based holonic event-driven architecture for autonomous networked manufacturing systems, IEEE Transactions on Automation Science and Engineering, 18(1), 2020, 205-215. https://doi.org/10.1109/TASE.2020.3025784

[6] Esmaeilian, B.; Sarkis, J.; Lewis, K.;Behdad, S.: Blockchain for the future of sustainable supply chain management in Industry 4.0, Resources, Conservation and Recycling, 163, 2020, 105064. https://doi.org/10.1016/j.resconrec.2020.105064

[7] Fierro, L. H.; Cano, R. E.; García, J. I.: Modelling of a multi-agent supply chain management system using Colored Petri Nets, Procedia Manufacturing, 42, 2020, 288-295 https://doi.org/10.1016/j.promfg.2020.02.095

[8] Gunduz, M. A.; Demir, S.; Paksoy, T.: Matching functions of supply chain management with smart and sustainable Tools: A novel hybrid BWM-QFD based method, Computers & Industrial Engineering, 162, 2021, 107676. https://doi.org/10.1016/j.cie.2021.107676

[9] https://github.com/gruizmer/ADAM-Data-Repository

[10] Jamrus, T.; Wang, H. K.; Chien, C. F.:Dynamic coordinated scheduling for supply chain under uncertain production time to empower smart production for Industry 3.5, Computers & Industrial Engineering, 142, 2020, 106375. https://doi.org/10.1016/j.cie.2020.106375

[11] Jiang, Z. Z.; He, N.; Qin, X.; Sun, M.; Wang, P.: Optimizing production and maintenance for the service-oriented manufacturing supply chain, Annals of Operations Research, 2020, 1-26. https://doi.org/10.1007/s10479-020-03758-7

[12] Kamiebisu, R.; Saso, T.; Nakao, J.; Liu, Z.; Nishi, T,; Matsuda, M.: Use cases of the platform for structuring a smart supply chain in discrete manufacturing, Procedia CIRP, 107, 2022, 687-692. https://doi.org/10.1016/j.procir.2022.05.046

[13] Khan, W. Z.; Rehman, M. H.; Zangoti, H. M.; Afzal, M. K.; Armi, N.; Salah, K. Industrial internet of things: Recent advances, enabling technologies and open challenges, Computers & Electrical Engineering, 81, 2020, 106522. https://doi.org/10.4018/978-1-7998-1230-2

[14] Kuo, T. C.; Chen, K. J.; Shiang, W. J.; Huang, P. B.; Otieno, W.; Chiu, M. C.: A collaborative data-driven analytics of material resource management in smart supply chain by using a hybrid Industry 3.5 strategy, Resources, Conservation and Recycling, 164, 2021, 105160. https://doi.org/10.1016/j.resconrec.2020.105160

[15] Laili, Y.; Peng, C.; Chen, Z.; Ye, F.; Zhang, L.: Concurrent local search for process planning and scheduling in the industrial Internet-of-Things environment, Journal of Industrial Information Integration, 28, 2022, 100364. https://doi.org/10.1016/j.jii.2022.100364

[16] Lyu, M.; Li, X.; Chen, C. H.: Achieving Knowledge-as-a-Service in IIoT-driven smart manufacturing: A crowdsourcing-based continuous enrichment method for Industrial Knowledge Graph, Advanced Engineering Informatics, 51, 2022, 101494. https://doi.org/10.1016/j.aei.2021.101494

[17] Pardo, C.; Wei, R.; Ivens, B. S.: Integrating the business networks and internet of things perspectives: A system of systems (SoS) approach for industrial markets, Industrial Marketing Management, 104, 2022, 258-275. https://doi.org/10.1016/j.indmarman.2022.04.012

[18] Pu, Z.; Jiang, Q.; Yue, H.; Tsaptsinos, M.: Agent-based supply chain allocation model and its application in smart manufacturing enterprises, The Journal of Supercomputing, 76(5), 2020, 3188-3198. https://doi.org/10.1007/s11227-018-2536-x

[19] Qayyum, T.; Trabelsi, Z.; Waqar Malik, A.; Hayawi, K.: Mobility-aware hierarchical fog computing framework for Industrial Internet of Things (IIoT), Journal of Cloud Computing, 11(1), 2022, 1-17. https://doi.org/10.1186/s13677-022-00345-y

[20] Radanliev, P.; De Roure, D.; Nicolescu, R.; Huth, M.; Santos, O.: Artificial intelligence and the internet of things in industry 4.0, CCF Transactions on Pervasive Computing and Interaction, 3(3), 2021, 329-338 .https://doi.org/10.1007/s42486-021-00057-3

[21] Radanliev, P.; De Roure, D.; Page, K.; Nurse, J. R.; Mantilla Montalvo, R.; Santos, O.; Maddox, L.; Burnap, P. Cyber risk at the edge: Current and future trends on cyber risk analytics and artificial intelligence in the industrial internet of things and industry 4.0 supply chains, Cybersecurity, 3(1), 2020, 1-21. https://doi.org/10.1186/s42400-020-00052-8

[22] Sarkar, M.; Do Chung, B.: Controlling random lead time demand through a flexible production system under supply chain management, IEEE Access, 9, 2021, 112236-112256. https://doi.org/10.1109/ACCESS.2021.3103967

[23] Shao, X. F.; Liu, W.; Li, Y.; Chaudhry, H. R.; Yue, X. G.: Multistage implementation framework for smart supply chain management under industry 4.0, Technological Forecasting and Social Change, 162, 2021, 120354. https://doi.org/10.1016/j.techfore.2020.120354

[24] Toktaş-Palut, P.: Analyzing the effects of Industry 4.0 technologies and coordination on the sustainability of supply chains, Sustainable Production and Consumption, 30, 2022, 341-358. https://doi.org/10.1016/j.spc.2021.12.005

[25] Wu, Y.; Wang, Z.; Ma, Y.; Leung, V. C.: Deep reinforcement learning for blockchain in industrial IoT: A survey, Computer Networks, 191, 2021, 108004. https://doi.org/10.1016/j.comnet.2021.108004

[26] Xiang, C.; Li, B.: Research on ship intelligent manufacturing data monitoring and quality control system based on industrial Internet of Things, The International Journal of Advanced Manufacturing Technology, 107(3), 2020, 983-992. https://doi.org/10.1007/s00170-019-04208-w
[27] Xu, Z.; Zhang, J.; Song, Z.; Liu, Y.; Li, J.; Zhou, J.: A scheme for intelligent blockchain-based manufacturing industry supply chain management, Computing, 103(8), 2021, 1771-1790. https://doi.org/10.1007/s00607-020-00880-z
[28] Zhang, H.: Industrial cluster innovation based on 5 G network and internet of things, Microprocessors and Microsystems, 83, 2021, 103974. https://doi.org/10.1016/j.micpro.2021.103974
[29] Zhang, N.; Li, B.: Pricing and coordination of green closed-loop supply chain with fairness concerns, IEEE Access, 8, 2020, 224178-224189. https://doi.org/10.1109/ACCESS.2020.3045152
[30] Zhou, Z.; Liu, Y.; Yu, H.; Chen, Q.: Logistics supply chain information collaboration based on FPGA and internet of things system, Microprocessors and Microsystems, 80, 2021, 103589. https://doi.org/10.1016/j.micpro.2020.103589